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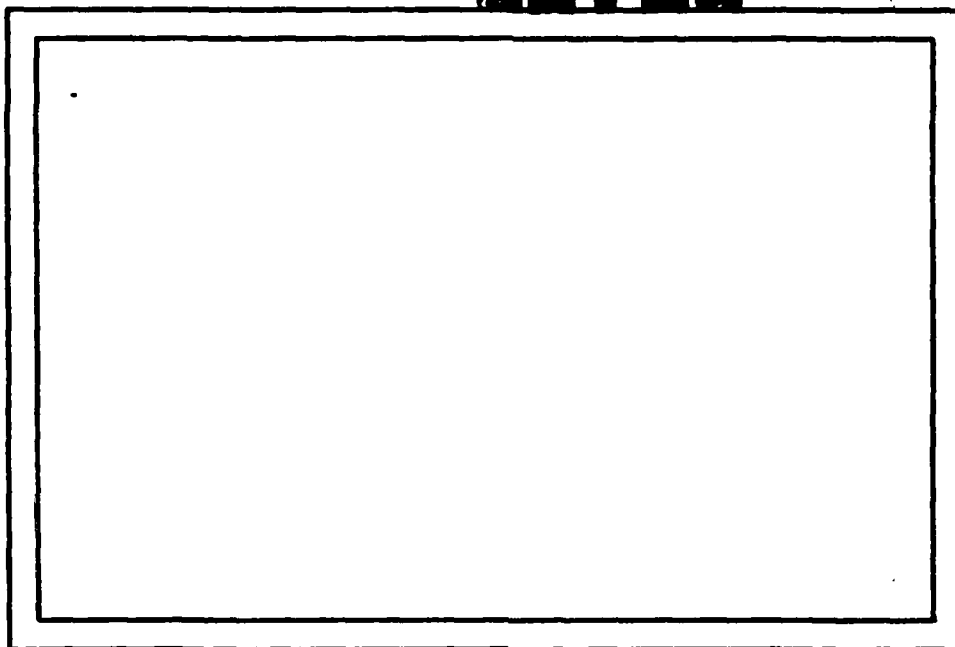UNCLASSIFIED   TR-988   AFOSR-TR-81-0144   NL

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⑥ MULTISPECTRAL TEXTURE.

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ABSTRACT

   Textures in single-band images are often characterized by
statistics of the joint distributions of pairs of gray levels
for pairs of pixels in given relative positions, or by statis-
tics of absolute gray level differences for such pairs of pixels.
Joint distributions of pairs of spectral vectors in multiband
images are cumbersome, since for k bands they are 2k-dimensional;
but absolute difference distributions are less so--e.g., for two
bands they are only two-dimensional. This paper discusses the
possibility of using statistics of absolute difference distri-
butions for characterizing textures in multiband images, with
emphasis on the two-band case.

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1. Introduction

Many different types of features have been used for texture analysis and classification; see [1] for a recent review. Essentially all of this work has dealt with single-band images rather than with color or multispectral images. When texture analysis is used for multispectral imagery, it is applied to a single band (possibly a composite of the original bands, or an "eigenband" resulting from a Karhunen-Loève transformation), and if desired, the results are treated as an additional "texture band"; but texture features are not commonly, if ever, measured for multiband data directly. The purpose of this paper is to introduce a class of texture features that are defined for multiband imagery, and that are computationally quite tractable in the two-band case.

The particular class of texture features which we will generalize to the multiband case are statistical features derived from pairs of pixels in given relative positions. For single-band images, the joint distribution of the gray levels of such a pair of pixels can be represented by a "co-occurrence matrix" which tabulates how often each possible pair of gray levels occurs in the image in the given relative position, and we can define texture features by computing various statistics from such matrices (e.g., moment of inertia about the main diagonal, entropy, etc.). This concept generalizes immediately to multiband images, but is computationally cumbersome; even in the two-band case, the joint distribution of pairs of 2-vectors in a given relative position requires a four-dimensional matrix for its representation, which is expensive in storage space unless

the values in the bands are very coarsely quantized. (It might be possible, in principle, to use sparse matrix techniques to handle high-dimensional co-occurrence matrices; but we shall not pursue this possibility here.)

An alternative to using joint distributions of pairs of pixel gray levels in given relative positions is to use only the distribution of absolute differences of such pairs of gray levels. It was seen in [2] that for some texture classification tasks, features based on such distributions are just as effective as features derived from joint gray level distributions. In the single-band case, an absolute difference distribution is represented by a (one-dimensional) histogram of the absolute differences, and we can define texture features by computing various statistics from such histograms -e.g., their means, variances, entropies, etc. In the two-band case, it would be represented by a two-dimensional scatter plot showing how often each (difference in band 1, difference in band 2) pair occurs for pixel pairs in the given relative position. Thus for small numbers of bands (two, especially), texture analysis based on absolute difference statistics is computationally quite tractable.

Section 2 of this paper defines a class of multiband texture features based on absolute difference statistics, and Section 3 gives examples of results obtained when these features are computed for some simple two-band textures.

2. Features

2.1 Single-based features

Let us first briefly review the definitions of co-occurence matrices and absolute difference histograms for single-band images. Let $\underline{\delta} \equiv (\Delta x, \Delta y)$ be a relative position vector, and let the gray levels of the given images be $0,1,\ldots,m-1$. The co-occurence matrix M_δ is an m-by-m matrix whose $(i,j)^{th}$ element is the number of pairs of pixels in relative position $\underline{\delta}$ that have the pair of gray levels (i,j). For a uniformly textured image having a given gray level probabilit_ density, concentration of high values near the main diagonal of M_δ suggests that the texture is composed of uniform patches that are large relative to $|\underline{\delta}|$ (implying that two gray levels $\underline{\delta}$ apart tend to be similar). Thus the moment of inertia of M_δ about its main diagonal is a measure of the "busyness" of the texture relative to $|\underline{\delta}|$. This is one simple example of how statistics computed form M_δ, for various $\underline{\delta}$'s, can provide information about the nature of the texture.

Similarly, the difference histogram D_δ is an m-vector whose k^{th} element is the number of pairs of pixels in relative position $\underline{\delta}$ that have absolute gray level difference k. Note that if we sum M_δ along lines parallel to its main diagonal, we obtain a difference histogram, but for signed rather than absolute differences; to obtain D_δ, we need only make M_δ symmetric by adding pairs of elements symmetric with respect to the main diagonal, and then summing the upper triangle of M_δ along lines parallel to the diagonal. Thus the moment of inertia of D_δ around the origin (k=0) is the same as the moment of inertia of M_δ around the main diagonal, indicating that D_δ's too can be used as a source

of texture features.

Co-occurence matrices and difference histograms are commonly computed for images whose gray level probability densities have been standardized, e.g., by histogram flattening. If this were not done, contrast effects would be confused with coarseness effects; if we increase the contrast of an image, its M_δ entries are spread outward from the main diagonal, and its D_δ entries from the origin.

2.2 Multiband features

The values of the pixels in a b-band image are b-vectors of the form $(Z_1, \ldots, Z_b)$, $0 \le Z_h \le m-1$, $1 \le h \le b$. Thus the b-band analog of a co-occurence matrix M_δ is a 2b-dimensional m by m...by m array whose $(i_1, \ldots, i_{2b})^{th}$ element is the number of pairs of pixels in relative position $\underline{\delta}$ that have the pair of b-vectors $((i_1, \ldots, i_b), (i_{b+1}, \ldots, i_{2b}))$ as values. Evidently, even for small values of m and b, such an M_δ is cumbersome to work with, e.g., for m=8 and b=2, it has $m^{2b} = 8^4 = 2^{12} = 4096$ elements, and this number grows rapidly with both m and b.

The situation is somewhat more manageable if we work with difference histograms rather than co-occurence matrices. A b-band difference histogram D_δ is a b-dimensional m by m...by m array whose $(k_1, \ldots, k_b)^{th}$ element is the number of pairs of pixels in relative position $\underline{\delta}$ that have the b-vector of absolute differences $(k_1, \ldots, k_b)$ in bands $1, \ldots, b$, respectively. The size of D_δ for small vlaues of b is quite manageable; e.g., for m=8 and b=2 it has only $m^b = 64$ elements.

Some insight into the possible forms of multiband scatter plots (again, for simplicity we assume b=2) can be obtained by

considering two simple hypothetical examples:

1) Suppose that the texture is composed of small patches on a background, where the patches and the background have a greater reflectivity difference in one band than in the other. For a given $\underline{\delta}$, smaller than the average patch size or spacing, the difference histogram in each band is a mixture of within-patch and within-background differences (presumably near 0) and patch-background differences (larger). In this case the two-dimensional D_δ scatter plot should consist of a cluster near $(0,0)$ and a cluster near (d_1,d_2), where d_1 and d_2 are the expected patch-background differences in the two bands.

2) Suppose that the texture arises from an undulating surface in which slope differences give rise to intensity differences in the image, and the change in intensity as a function of slope is different for the two bands. A given displacement $\underline{\delta}$ corresponds to a given expected slope difference, hence to a pair of expected intensity differences in the two bands.

Note that in both of these cases, the differences in the two bands are quite correlated.

What types of statistics would it be useful to measure for b-band M_δ's and D_δ's? (We shall assume, for convenience, that the probability densities of values have been standardized, e.g., by histogram flattening of each band.) Evidently, the spread of values relative to the main diagonal or origin is still relevant, but we should be able to analyze it in greater detail, since it has more degrees of freedom. For simplicity, let us consider only D_δ's and only the two-band case. In this case D_δ is a two-dimensional array whose (i,j) element is the number of pairs of pixels in relative position $\underline{\delta}$ that have absolute difference i in the first band and j in the second band. We can make the following qualitative observations about such an array:

a) The spread of values away from the origin is a
    measure of texture "busyness", since high values
    far from the origin imply frequent occurrence of
    high absolute differences in one or both bands.

b) The spread of values away from the main diagonal
    (as measured, e.g., by the moment of inertia of
    D_δ about the diagonal) is a measure of relative
    texture "busyness" in the two bands; high values
    far from the diagonal imply many cases where one
    absolute difference is quite different from the
    other.

c) The asymmetry of the values relative to the main
    diagonal (as measured, e.g., by the slope of the
    principal axis of D_δ relative to the diagonal
    direction) indicates which of the two bands is
    "busyer".

Analogous remarks can be made about the b-band case for $b>2$.

Evidently, measures such as (b-c) can only be obtained from

a two-band scatter plot such as D_δ; they could not be derived

by analyzing the two bands separately, since they measure the

correlatedness of the absolute difference values between the

bands. Thus it is clear that texture features based on two-band

D_δ's can provide information about the texture not available

from single-band texture features. This means that in principle,

there exist pairs of two-band textures that can be discriminated

easily when features based on two-band D_δ's are used, but that

are hard to discriminate based on single-band features. Of course,

this does not imply that such pairs of textures will be very

common; it may be difficult to find such examples.

3. Examples

The following examples are based on a class of synthetic single-band textures derived from stationary random field models having given types of neighbor dependence [3]. Three examples of textures generated by such models are shown in Figure 1.

Artificial two-band textures were created from these single-band textures as follows: let T be a given single-band texture, and let T_i be the two-band texture whose bands are T and T shifted by the amount $\underline{\delta}_i$. The smaller $|\underline{\delta}_i|$ (relative to the neighborhood used in defining T), the more these two bands should be correlated. Thus if we consider a set of two-band textures T_i having $|\underline{\delta}_i|$'s of various sizes, we should obtain rather different two-band scatter plots D_δ when $|\underline{\delta}|$ is small.

Figure 2 shows examples of the D_δ plots obtained for the synthetic textures in Figure 1, using $\underline{\delta}_1=(1,0)$, $\underline{\delta}_2=(2,0)$, $\underline{\delta}_3=(4,0)$, and $\underline{\delta}=(1,0)$. We see that the scatter plots are indeed rather different for the different $\underline{\delta}_i$'s. To quantify this difference, Table 1 shows the values of two statistics measured for these scatter plots: the sum of the squares of the values ("ASM") and the moment of inertia about the 45° diagonal ("CON") [1,2].

4. Concluding remarks

Two-band texture features have the potential of providing textural information that is not available from single-band features. Unfortunately, it is hard to find real examples of texture pairs which are discriminable on the basis of two-band features and not on the basis of single-band features; we have therefore shown only synthetic examples here. But if other investigators experiment with two-band features, cases should eventually be discovered in which the potential power of the two-band approach is realized.

References

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2. J.S. Weszka, C.R. Dyer, and A. Rosenfeld, A comparative study of texture features for terrain classification, IEEE Trans. SMC-6, 1976, 269-285.

3. R. Chellappa, Fitting random field models to images, TR-928, Computer Vision Laboratory, Computer Science Center, University of Maryland, August 1980.

Texture	Relative displadement of "bands"	$ASM \times 10^3$	CON
(a)	1	4.0	530
	2	4.4	532
	4	4.6	458
(b)	1	2.1	103
	2	2.4	64
	4	2.2	75
(c)	1	1.1	123
	2	1.0	295
	4	1.0	198

Table 1.   ASM and CON statistics for the D_δ plots in
Figure 2.

(a)

(b)

(c)

Figure 1.   Three textures generated by stationary random
            field models [3].
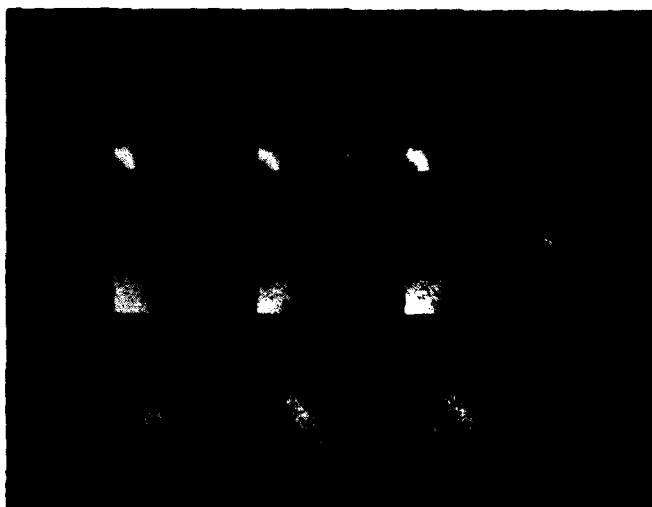
(a)

(b)

(c)

Figure 2. D_δ plots for two-band textures derived from the
            textures in Figure 1; one "band" is cyclically
            shifted relative to the other by 1, 2 or 4 pixels
            to produce the plots in the left, center, and right
            columns, respectively.

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Textures in single-band images are often characterized by statistics of the joint distributions of pairs of gray levels for pairs of pixels in given relative positions, or by statistics of absolute gray level differences for such pairs of pixels. Joint distributions of pairs of spectral vectors in multiband images are cumbersome, since for k bands they are 2k-dimensional; but absolute difference distributions are less so -e.g., for two bands they are only

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